

Computation of pseudospectra

Vladimír Janovský, Dáša Janovská,
Kunio Tanabe

Outline:

- **Pseudospectra: concept**
- **Computing pseudospectra: the current approaches**
- **Predictor-corrector type method**
- **Implementation**
- **Experiments**
- **Conclusions**

Trefethen: Acta Numerica, 8 (1999)

Trefethen, Embree: *Spectra and Pseudospectra ...*, 2005.

$A \in \mathbb{C}^{n \times n}$... **non-normal**: the classical spectral information
may be misleading

Effects:

- transient growth for A^k (discrete time stability)
- transient growth for $\exp(t * A)$ (continuous time stability)
- ill-conditioned eigenvalue computations
- convergence of matrix iterations

Remedies?

Computing pseudospectra: early warning

$\forall \varepsilon > 0$, ε -**pseudospectrum** of \mathbf{A}

- the subset of the complex plane bounded by the ε^{-1} level curve of the resolvent norm:

$$\Lambda_\varepsilon(\mathbf{A}) = \{z \in \mathcal{C} : \|(z\mathbf{I} - \mathbf{A})^{-1}\| > \varepsilon^{-1}\}$$

- the set of all complex numbers that are in the spectrum of some matrix obtained by a perturbation of norm at most ε :

$$\Lambda_\varepsilon(\mathbf{A}) = \{z \in \mathcal{C} : z \in \Lambda(\mathbf{A} + \mathbf{E}) \text{ for some } \mathbf{E} \text{ with } \|\mathbf{E}\| < \varepsilon\}$$

- the sets in the z -plane bounded by level curves of the function

$$\Lambda_\varepsilon(\mathbf{A}) = \{z \in \mathcal{C} : \sigma_{\min}(z\mathbf{I} - \mathbf{A}) < \varepsilon\}$$

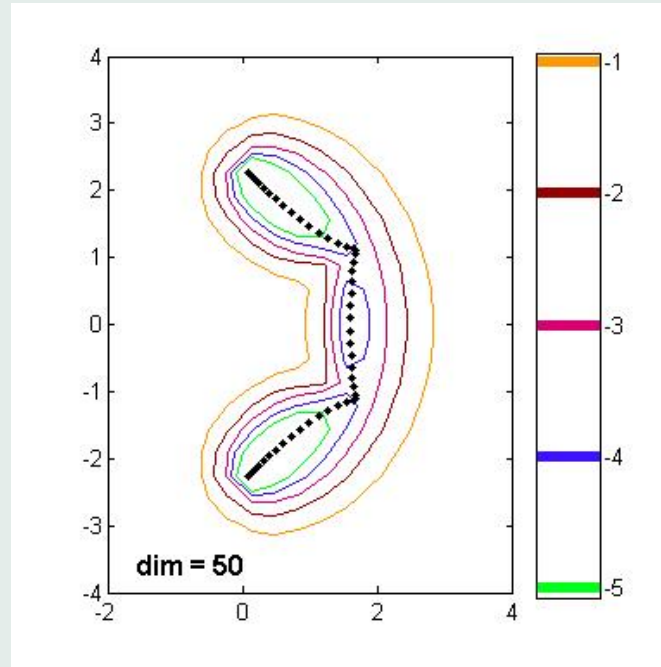
$\sigma_{\min}(z\mathbf{I} - \mathbf{A}) \dots$ the smallest singular value of $(z\mathbf{I} - \mathbf{A})$

\Rightarrow find contours

$$\partial\Lambda_\varepsilon(\mathbf{A}) = \{z \in \mathcal{C} : \sigma_{\min}(z\mathbf{I} - \mathbf{A}) = \varepsilon\}$$

Example: Grcar, $n = 50$

see <http://www.comlab.ox.ac.uk/pseudospectra/eigtool>



```
opts.npts = 24 ; opts.levels = [-1,-2,-3,-4,-5] ; opts.ax = [-2 4 -4 4];  
[x,y] = eigtool(A,opts,figure(1))
```

Computing pseudospectra

- [Grid techniques](#)

Trefethen: *Acta Numerica*, 8 (1999)

Wright: *Eigtool ...*, <http://www.comlab.ox.ac.uk/pseudospectra/eigtool>.

- [Curve-tracing techniques](#)

Brühl: *BIT*, 36 (1996)

Bekas, Gallopoulos: *Parallel Computing*, 27 (2001)

Mezher, Philippe: *Numer. Alg.* 29 (2002)

Burke, Lewis, Overton: *IMA J. Numer. Anal.*, 23 (2003)

Bekas, Gallopoulos, Simoncini: submitted

Ad grid techniques: Select the levels i.e., the values of ϵ .

1. Construct a mesh D in the complex plane \mathbb{C} .
2. Compute $\sigma_{\min}(zI - A)$ at each grid point $z \in D$.
3. Consider the level sets

$$\partial\Lambda_{\epsilon} = \{z \in \mathbb{C} : \sigma_{\min}(zI - A) = \epsilon\}$$

for the selected values of ϵ . Visualize them as the **contour plots** on the grid.

Ad 2:

inverse iterations ... $(zI - A)^(zI - A)$*

inverse Lanczos iterations ... $(zI - A)$

Ad curve-tracing techniques:

Theorem [Sun, Brühl]: Consider $z_0 \in \partial\Lambda_\epsilon$.

Let σ_{\min} be *simple* singular value of $z_0I - A$. Then $\partial\Lambda_\epsilon$ is a **real analytic curve** in a neighborhood of z_0 .

Let u_{\min} and v_{\min} be the relevant left and right singular vectors. Then $iv_{\min}u_{\min}/|v_{\min}u_{\min}|$ defines the anticlockwise oriented **tangent direction** at z_0 .

Def: Given $z \in \mathbb{C}$, we will call

(σ, u, v) a **singular triplet** of the matrix $zI - A$ provided that

σ is a singular value of $zI - A$,

$u \in \mathbb{C}^n$ and $v \in \mathbb{C}^n$

are the relevant left and right singular vectors

Def: Given $z \in \mathbb{C}$, we will call

(σ, u, v) a **minimum singular triplet** of the matrix $zI - A$ provided that

σ is the smallest singular value of $zI - A$,

$u \in \mathbb{C}^n$ and $v \in \mathbb{C}^n$

are the relevant left and right singular vectors

Algorithm [Brühl]: Let $z_0 \in \partial\Lambda_\epsilon$. Given a fixed step size τ , generate a sequence $z_k \in \mathbb{C}$ recursively as $z_{k-1} \mapsto z_k$,

$(\sigma, u, v) =$ minimum singular triplet of $z_0 I - A$ % initialization

repeat

$\hat{z}_k = z_{k-1} + \tau i (v^* u) / |v^* u|$ % predictor step

$(\sigma, u, v) =$ minimum singular triplet of $\hat{z}_k I - A$

$z_k = \hat{z}_k - (\sigma - \epsilon) / (u^* v)$ % corrector step

until the contour is completed

Algorithm [Bekas, Gallopoulos] ... "Cobra", a parallel version of [Brühl]

Algorithm [Bekas, Gallopoulos, Simoncini] ... the projected "Cobra"
(the transfer function methodology implemented)

Shortcomings:

- the step size control ?
- the guaranteed tolerance computation ?
- the check-closed curve control ?



an alternative **curve-tracing technique**:

Problem: Given $A \in \mathbb{C}^{n \times n}$, follow the contours

$$\partial\Lambda_\epsilon = \{z | \sigma_{\min}(zI - A) = \epsilon\}$$

The claim: After a "realification" and some transformations, we consider a curve

$$f : \mathbb{R}^{2+4n} \longrightarrow \mathbb{R}^{1+4n}.$$

The coordinates of the state space \mathbb{R}^{2+4n} are interpreted as

- the parameter $z \in \mathbb{C}$
- $u, v \in \mathbb{C}^n$, respectively, are the right/left singular vectors of $(zI - A)$, related to $\sigma_{\min}(zI - A) = \epsilon$.

The pathfollowing f yields the contours $\partial\Lambda_\epsilon$.

Continuation idea

Let $B \in \mathbb{C}^{n \times n}$. Consider a *singular triplet* (σ, u, v) , $\sigma \in \mathbb{R}$, $\sigma \geq 0$, $u \in \mathbb{C}^n$, $v \in \mathbb{C}^n$ of the matrix B :

$$Bv = \sigma u, \quad B^*u = \sigma v$$

and the *scaling conditions*

$$v^*v = 1, \quad u^*u = 1.$$

Note that

$$\sigma u^*u = u^*Bv = (u^*Bv)^* = v^*B^*u = \sigma v^*v.$$

Hence, if $\sigma > 0$, the scaling is equivalent to

$$\Re(v^*v) = 1.$$

(or $\Re(u^*u) = 1$ or $\Re(v^*v) + \Re(u^*u) = 2$, etc.)

Context: $B \equiv (zI - A)$, $z = x + iy$.

Let us set $\sigma = \epsilon \dots$ a fixed **positive** parameter,

$$u = \Re u + i\Im u, \quad v = \Re v + i\Im v,$$

$$f : \mathbb{R}^{2+4n} \longrightarrow \mathbb{R}^{1+4n},$$

$$\xi \equiv (x, y, \Re u, \Im u, \Re v, \Im v) \in \mathbb{R}^{2+4n},$$

$$f(\xi) = f(x, y, \Re u, \Im u, \Re v, \Im v) \in \mathbb{R}^{1+4n} \equiv$$

$$f_1(\xi) = -\epsilon \begin{bmatrix} \Re u \\ \Im u \end{bmatrix} + \begin{bmatrix} xI - \Re A & , & -yI + \Im A \\ yI - \Im A & , & xI - \Re A \end{bmatrix} \begin{bmatrix} \Re v \\ \Im v \end{bmatrix}$$

$$f_2(\xi) = -\epsilon \begin{bmatrix} \Re v \\ \Im v \end{bmatrix} + \begin{bmatrix} xI - \Re A^T, & yI - \Im A^T \\ -yI + \Im A^T, & xI - \Re A^T \end{bmatrix} \begin{bmatrix} \Re u \\ \Im u \end{bmatrix}$$

$$f_3(\xi) = (\Re v)^T \Re v + \Im v^T \Im v - 1.$$

Generically, the equation

$$f(\xi) = f(x, y, \Re u, \Im u, \Re v, \Im v) = 0$$

defines a curve in \mathbb{R}^{2+4n} .

Solutions of the equation are **stratified**: Let be the curve corresponding to the k -th singular value (set to the fixed ϵ) for $1 \leq k \leq n$ e.g., $k = 1$ for the largest and $k = n$ for the **smallest singular value**.

Let $z \in \partial\Lambda_\epsilon$ satisfy the assumption of Theorem.

$\implies f(\xi) = 0$, where $\xi = (x, y, \Re u, \Im u, \Re v, \Im v)$, $x + iy = z$,
 $\epsilon = \sigma_{\min}((x + iy)I - A)$, $u_{\min} = \Re u + i\Im u$, $v_{\min} = \Re v + i\Im v$.
Hence, ξ is related to a minimum singular triplet $(\epsilon, u_{\min}, v_{\min})$.

Theorem $\implies f(\xi(s)) = 0$, s ... parameter (e.g. the *arclength*)

$$x(s) + iy(s) = z(s), \quad \epsilon = \sigma_{\min}((x(s) + iy(s))I - A), \\ (\epsilon, u_{\min}(s), v_{\min}(s)).$$

Computational tool: **path following**

$$f : \mathbb{R}^{2+4n} \longrightarrow \mathbb{R}^{1+4n}$$

via a **predictor-corrector** technique.

Allgower, Georg: *Numerical continuation methods*, 1990.

Deufhard: *Newton Methods for Nonlinear Problems ...* , 2004.

Linearization: computing **oriented tangent**

Let $Df(\xi) \in \mathbb{R}^{(1+4n) \times (2+4n)}$ be differential of f at ξ .

Let $\delta\xi \in \mathbb{R}^{2+4n}$:

$$Df(\xi) \delta\xi = 0, \quad \delta\xi^T \delta\xi = 1$$

... a *tangent*

Let $(\delta x; \delta y) \in \mathbb{R}^2$ denote the first two components of $\delta\xi \in \mathbb{R}^{2+4n}$:

$$\det \begin{bmatrix} \delta x & \delta y \\ \Re(v_{\min}^* u_{\min}) & \Im(v_{\min}^* u_{\min}) \end{bmatrix} > 0.$$

... the *positively oriented tangent*

Here, $\xi \longleftrightarrow x + iy = z, (\epsilon, u_{\min}, v_{\min})$.

A starting point?

Problem: Given $\epsilon > 0$, find a point $z_0 = x_0 + iy_0$, $z_0 \in \partial\Lambda_\epsilon$.

Consider $(x_{\text{try}}; y_{\text{try}}) \in \mathbb{R}^2$, $z_{\text{try}} = x_{\text{try}} + iy_{\text{try}} \in \mathbb{C}$,
to be an **initial guess** of a point on $\partial\Lambda_\epsilon$.

- Compute a minimum singular triplet $(\sigma_{\min}, u_{\min}, v_{\min})$ of the matrix $z_{\text{try}}I - A$.
- Set $\xi_{\text{try}} \equiv (x_{\text{try}}, y_{\text{try}}, \Re u_{\min}, \Im u_{\min}, \Re v_{\min}, \Im v_{\min}) \in \mathbb{R}^{2+4n}$.
Define f with ϵ being set to $\epsilon \equiv \sigma_{\min}$. Hence, $f(\xi_{\text{try}}) = 0$.
Construct positively oriented tangent $\delta\xi_{\text{try}}$ at ξ_{try} .
- Consider f where ϵ is set to be the given $\epsilon > 0$. The iterations

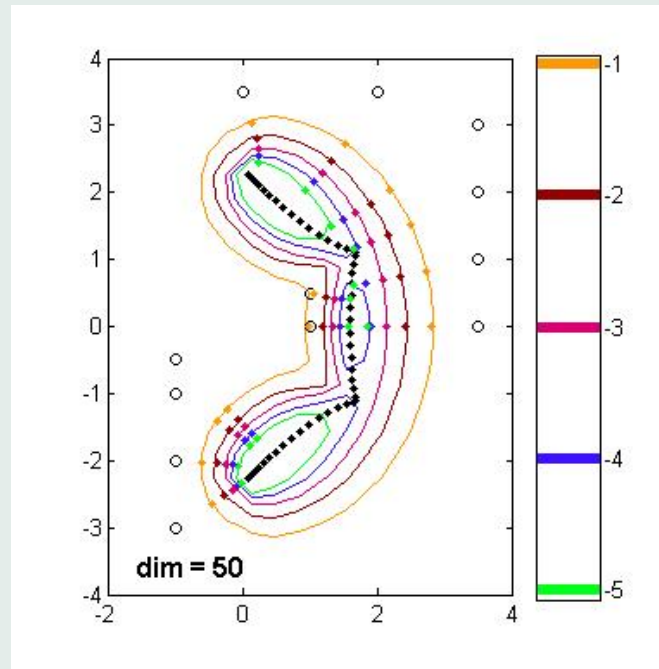
$$\xi \rightarrow \xi - \begin{bmatrix} Df(\xi) \\ \delta\xi_{\text{try}}^T \end{bmatrix} f(\xi),$$

started at ξ_{try} , are locally (quadratically) convergent to a point $\xi_0 \in \mathbb{R}^{2+4n}$, $f(\xi_0) = 0$.

- Let $(x_0; y_0) \in \mathbb{R}^2$... the first two components of ξ_0 .
Let $z_0 \equiv x_0 + iy_0$. Then $z_0 \in \partial\Lambda_\epsilon$.

Example-continued: Grcar, $n = 50$

testing the starting points



black circles ... $z_{try} = x_{try} + iy_{try} \in \mathbb{C}$

coloured points ... the targets of the iterations, $z_0 \in \partial\Lambda_\epsilon$
according to the scale $\epsilon = 10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}$

Computations on Intel T2300 1.66 GHz, dual core Centrino, using MATLAB version 7.1.

Toolbox MATCONT: A continuation software in Matlab
Dhooge, Govaerts, Kuzetsov: ACM Trans. Math. Software, 31 (2003)

Given $\epsilon > 0$: ... pointwise approximations of closed curves

$$x \equiv \{\xi_0, \xi_1, \dots, \xi_j, \xi_{j+1}, \dots, \xi_N\}, \quad v \equiv \{\delta\xi_0, \delta\xi_1, \dots, \delta\xi_j, \delta\xi_{j+1}, \dots, \delta\xi_N\},$$

$\xi_j \in \mathbb{R}^{2+4n}$: $f(\xi_j) = 0$, $\delta\xi_j \in \mathbb{R}^{2+4n}$... positively oriented tangent, and

$$h \equiv \{\tau_0, \tau_1, \dots, \tau_j, \tau_{j+1}, \dots, \tau_N\}$$

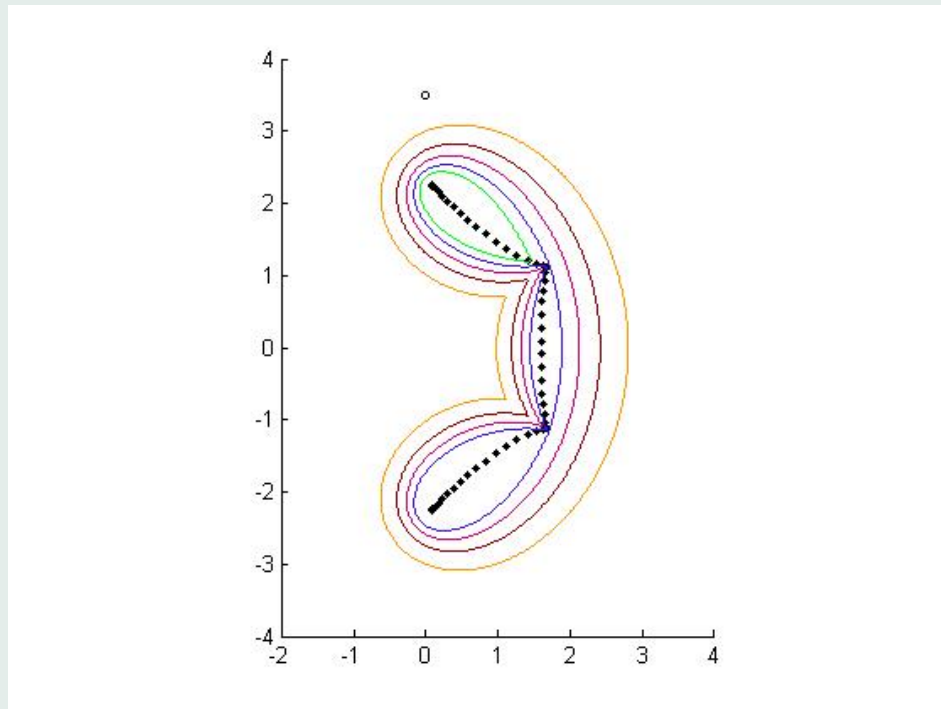
... the step-size τ_j at the j -th step

predictor-corrector algorithm: the recurrence

$$\xi_j, \delta\xi_j, \tau_j \longmapsto \xi_{j+1}, \delta\xi_{j+1}, \tau_{j+1}.$$

Example-continued: Grcar, $n = 50$

Pathfollowing the level curves

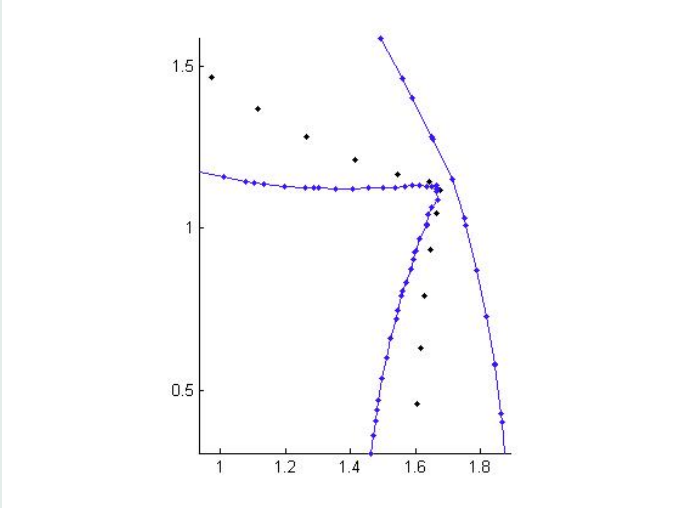
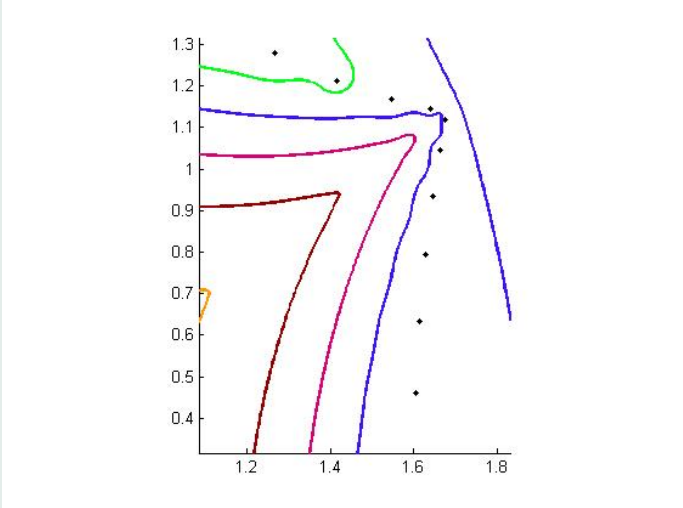


blue ... $\epsilon = 10^{-4}$

Closed curve detected at step 227

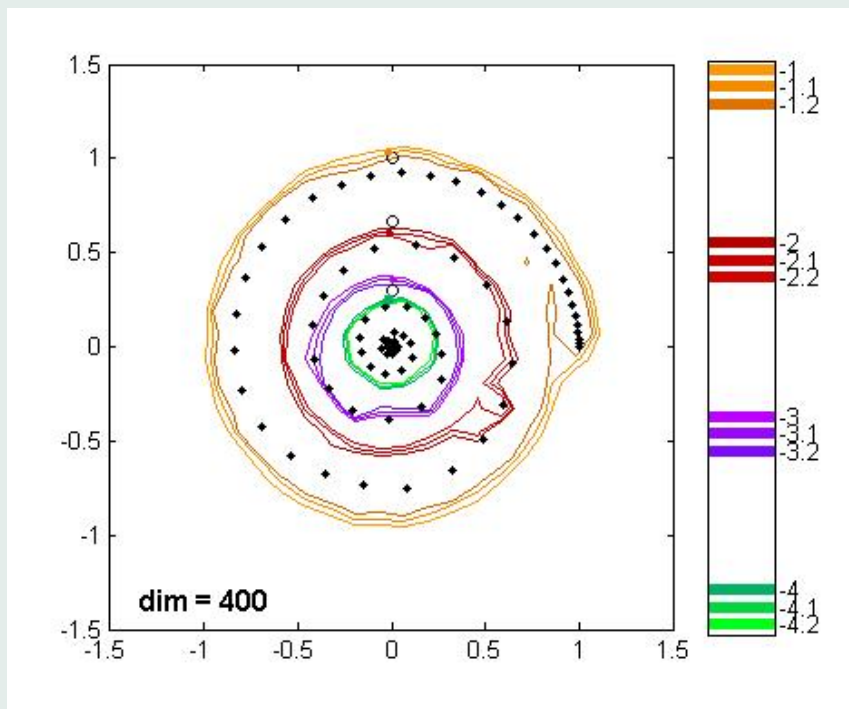
elapsed time = 17.3 secs, npoints curve = 227

Pathfollowing the level curves - zoom



blue ... $\epsilon = 10^{-4}$

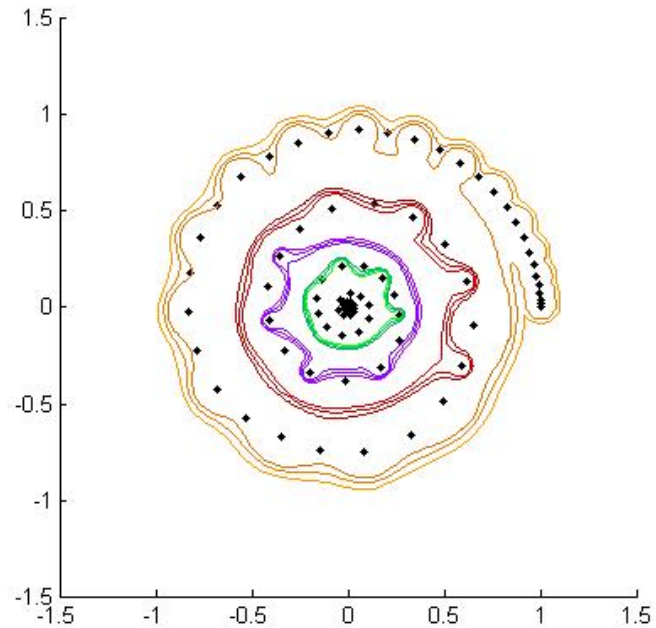
Example: Landau, $n = 400$



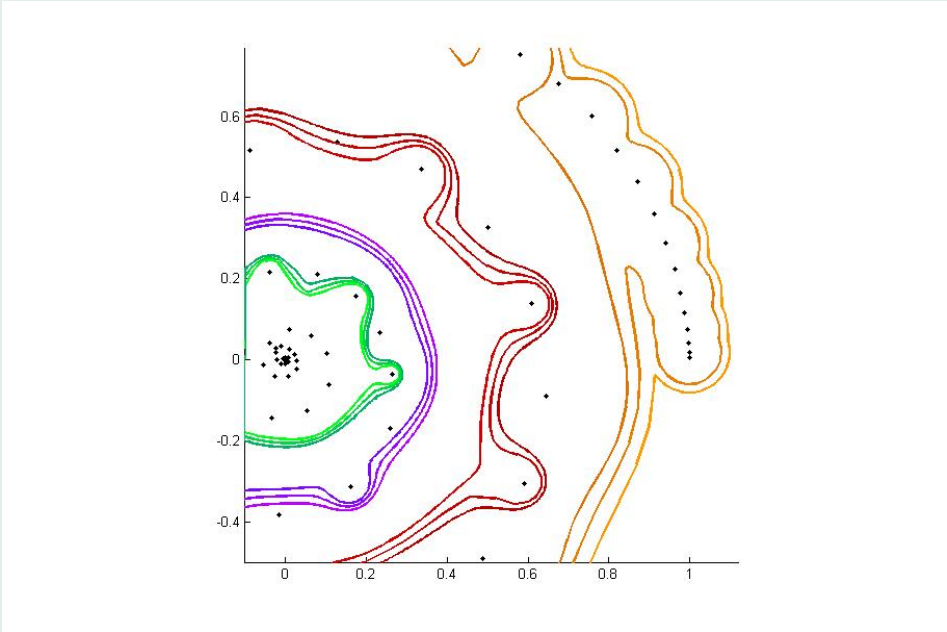
```
opts.npts = 24 ;  
opts.levels = [-1,-1.1,-1.2,-2,-2.1,-2.2,-3,-3.1,-3.2,-4,-4.1,-4.2];  
[x,y] = eigtool(A,opts,figure(1))
```

Example: Landau, $n = 400$

Pathfollowing the level curves



Pathfollowing the level curves - zoom



Conclusions

- Given a matrix $A \in \mathbb{C}^{n \times n}$, we compute the branch consisting of a fixed singular value ϵ and corresponding left and right singular vectors of parameter dependent matrix $(x + iy)I - A$.
- The fact that the branch corresponds to the smallest singular value $\sigma_{\min}((x + iy)I - A) = \epsilon$ is sufficient to verify at just one point of the branch due to continuity argument.

- Formulation: Implicitly defined curve

$$f : \mathbb{R}^{2+4n} \longrightarrow \mathbb{R}^{1+4n} .$$

- Computational technique: the classical **predictor-corrector**. We can exploit standard ready-made software, just supply particular definitions of $f(\xi)$ and $Df(\xi)$.

Hence, we may take advantage of the standard

- step size control
- guaranteed tolerance computation
- check-closed curve control

Supplemets

- **Gallery**
- **Twists** of u 's and v 's
- **Singularites ?**

- Ad **Gallery**

Gallery

[1] Trefethen, Embree: *Spectra and Pseudospectra ...*, 2005.

[2] Wright: *Eigtool ...*, <http://www.comlab.ox.ac.uk/pseudospectra/eigtool>.

Landau, $n = 400$, $A \in \mathbb{C}^{400 \times 400}$ is a full matrix

see Landau Demo in [2].

Motivation: see [1] § 60 (Landau: high-power lasers, unstable resonators)

Grcar, $n = 500$, $A \in \mathbb{R}^{500 \times 400}$ is a sparse Toeplitz matrix

see [1] § 7, p. 58.

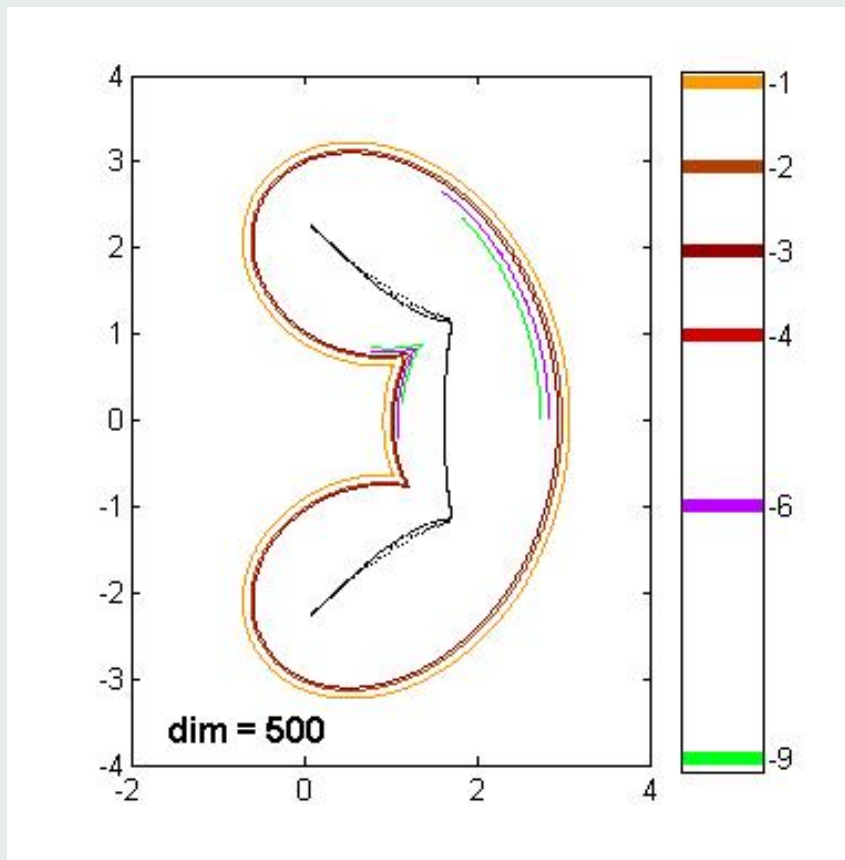
Orr-Sommerfeld matrix, $n = 99$, $A \in \mathbb{C}^{99 \times 99}$ is a full matrix.

see Orr-Sommerfeld Demo in [2].

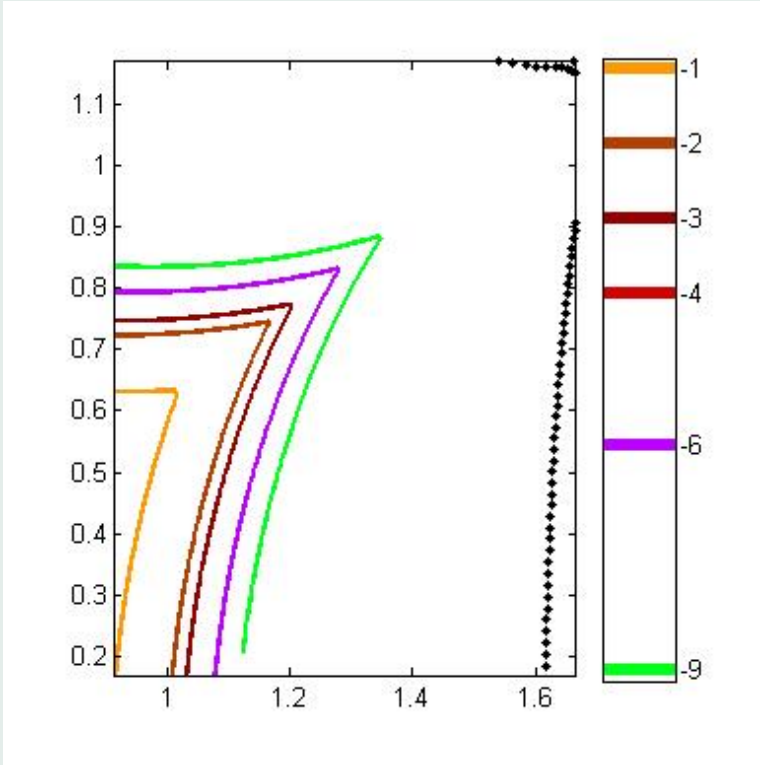
Motivation: see [1] § 22 (plane Poiseuille flow, Orr-Sommerfeld equation)

Example: Gr_{car}, $n = 500$

Pathfollowing the level curves

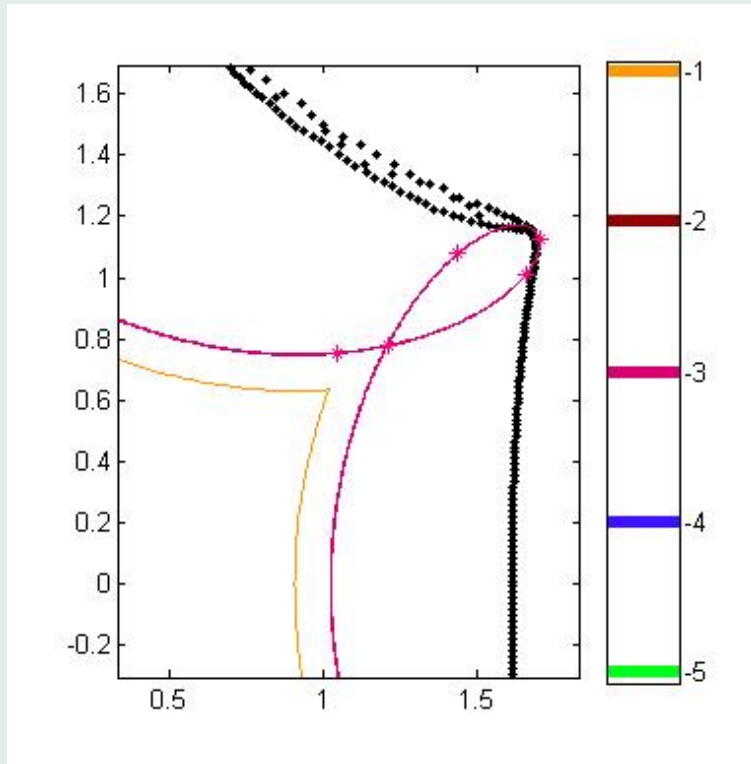


Pathfollowing the level curves - zoom



Pathfollowing the level curves - a numerical artefact

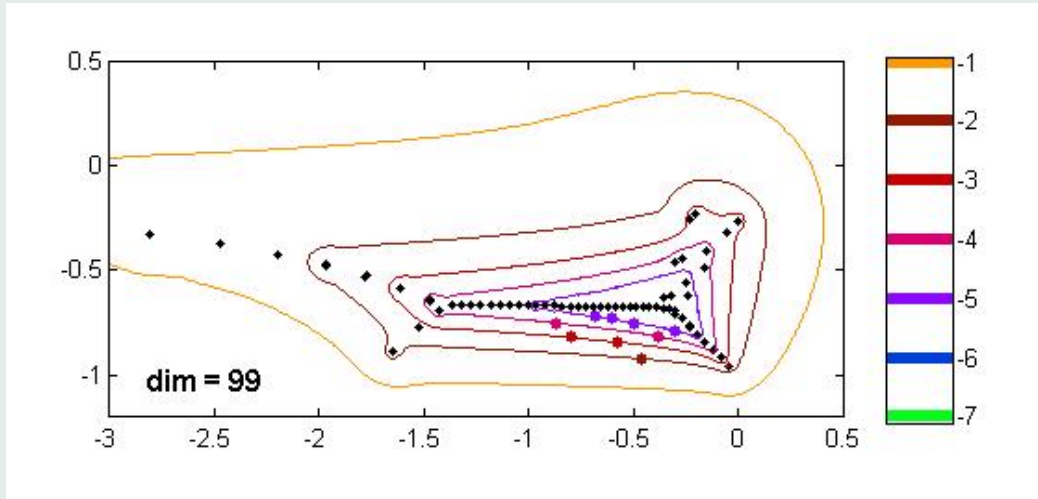
```
opt = contset(opt, 'MaxStepsize', 1);
```



$\epsilon = 10^{-1}$... O.K., $\epsilon = 10^{-3}$... the quirk

Example: Orr-Sommerfeld, $n = 99$

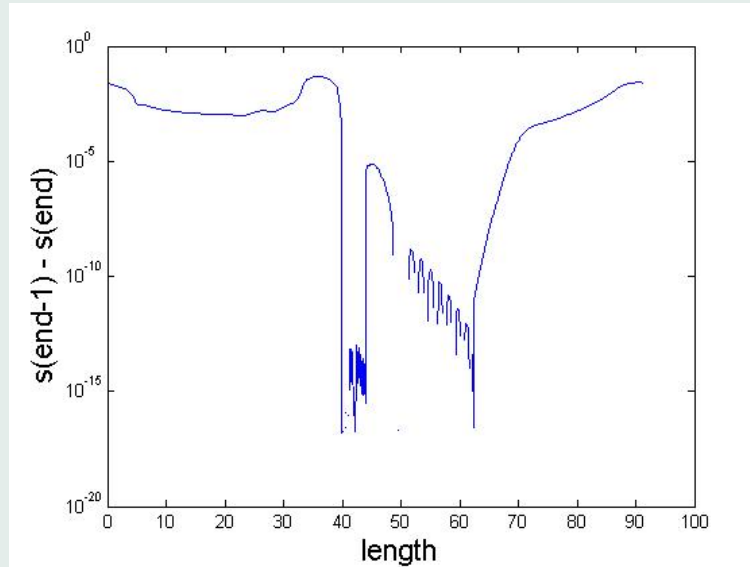
Pathfollowing the level curves



no success for $\epsilon = 10^{-6}, 10^{-7}$

restarts for $\epsilon = 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}$ marked by dots

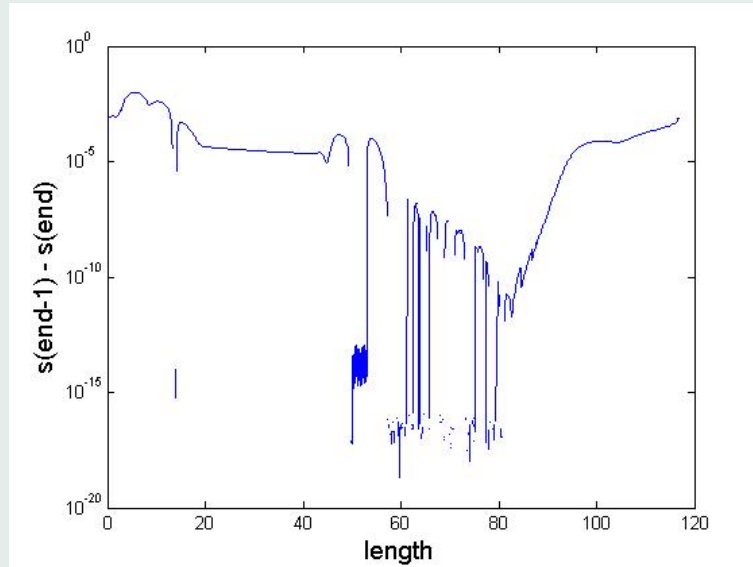
Restarts: explanation



$$\epsilon = 10^{-2}$$

Next to the smallest $s(\text{end}-1)$ minus
the smallest singular value $s(\text{end}) \equiv 10^{-2}$
vs the position on the path.

Restarts: explanation



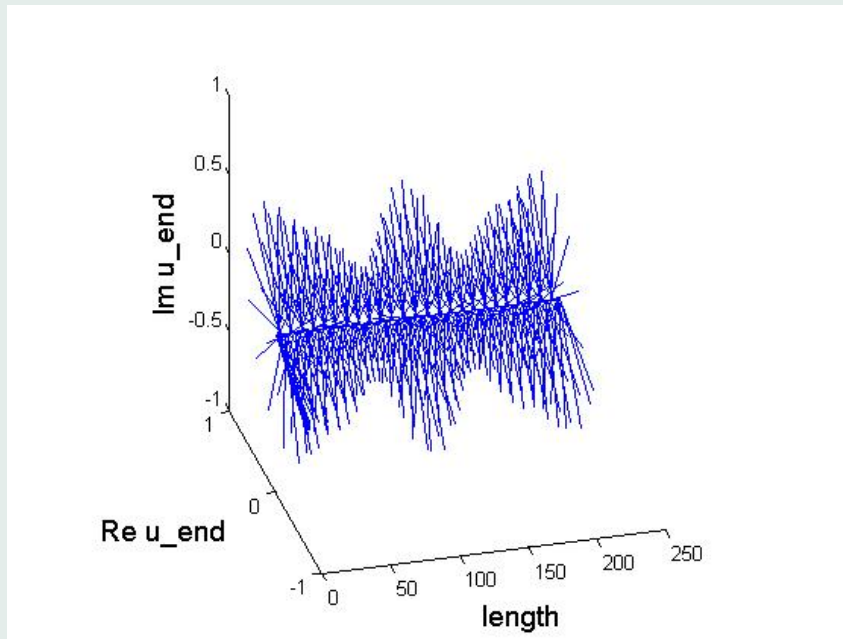
$$\epsilon = 10^{-3}$$

Next to the smallest $s(\text{end}-1)$ minus
the smallest singular value $s(\text{end}) \equiv 10^{-2}$
vs the position on the path.

- Ad **Twists** of u 's and v 's

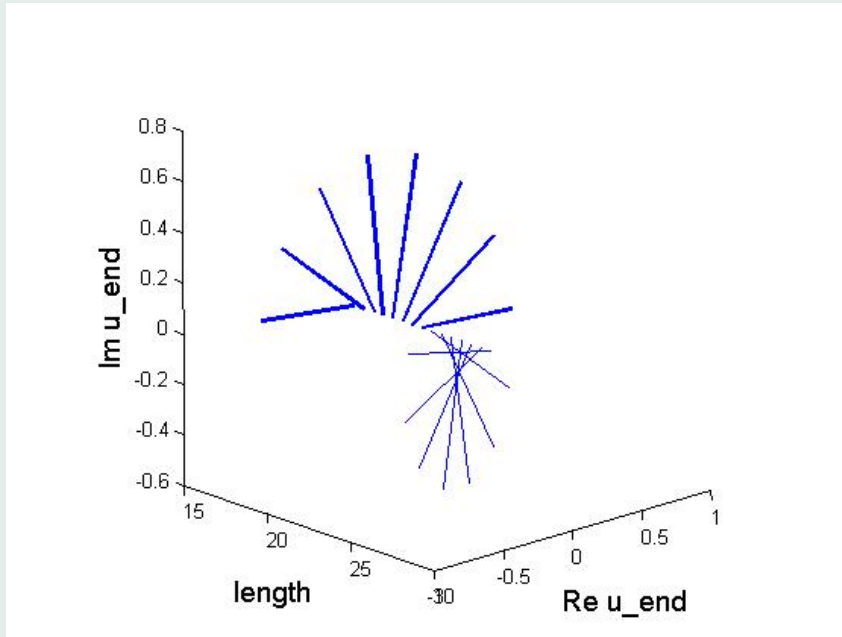
Example: Grcar, $n = 50$

The left singular vector $u \in \mathbb{C}^{50}$:
the last component $u_{50} = \Re u_{50} + i \Im u_{50}$ vs the arclength.



$\log_{10} \epsilon = -4.1$, $z_0 = 1.4601 - i0.0132$.

Ad: The last component $u_{50} = \Re u_{50} + i\Im u_{50}$ vs the arclength.

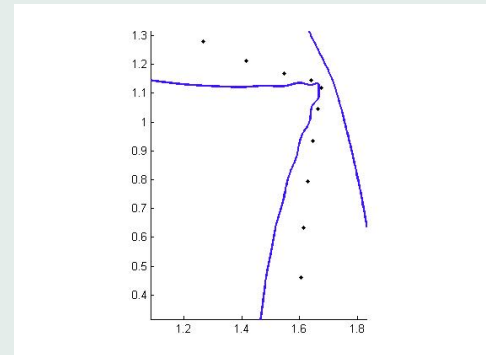
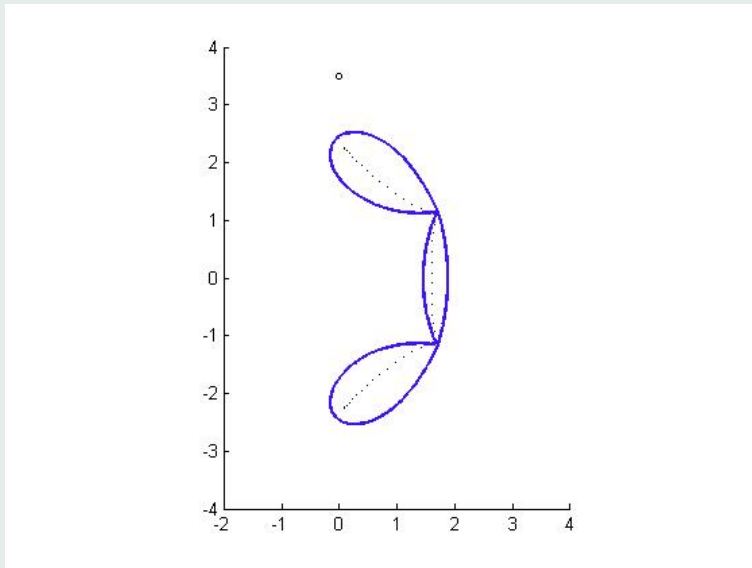


The zoom of the segment $17 \leq \text{length} \leq 25$.

- Ad **Singularites** ?

Grcar, $n = 50$

Pathfollowing the level curves

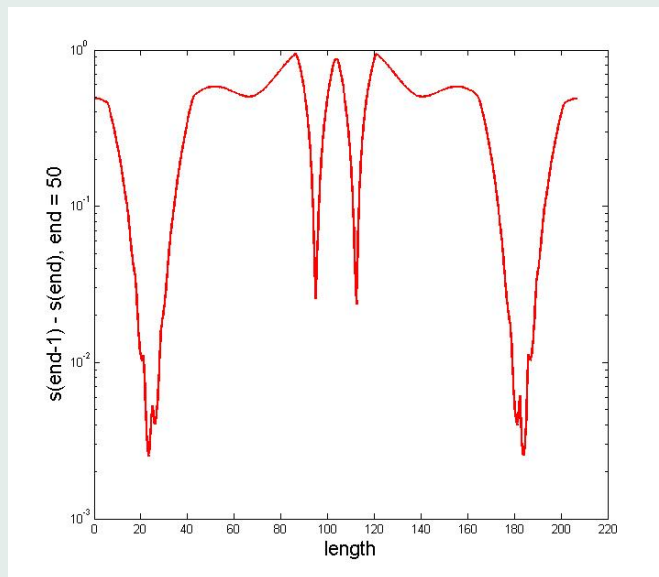


blue ... $\epsilon = 10^{-4}$

Closed curve detected at step 227

elapsed time = 17.3 secs, npoints curve = 227

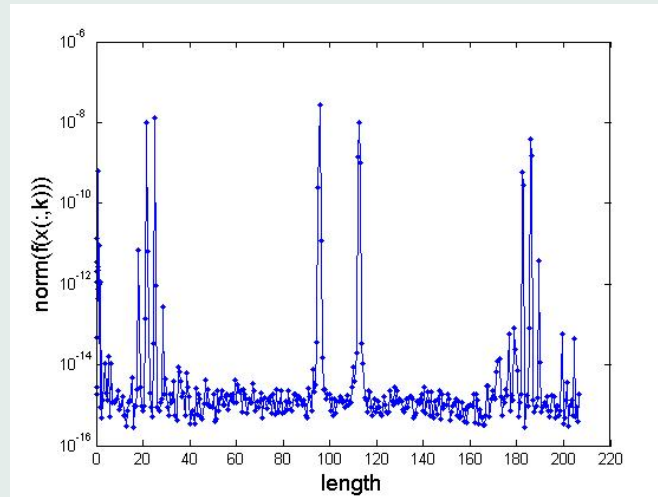
Singularities?



$k \rightarrow x(:, k) \rightarrow [U, S, V] = svd(A - (x(1, k) + i * x(2, k)) * eye(n, n)) \rightarrow$
 $\rightarrow \{s(n) \equiv \varepsilon, s(n-1)\} \rightarrow s(n-1) - s(n)$

$k \rightarrow arclength$

Residuum: $1 \leq k \leq 227$, $k \rightarrow \text{arclength}$,
 $k \rightarrow \left\{ z \in \mathbb{C}, u \in \mathbb{C}^{50}, v \in \mathbb{C}^{50} \right\} \equiv x \rightarrow f(x) \rightarrow \text{norm}(f(x))$



```
opt=contset(opt,'MaxStepsize', 1);  
opt=contset(opt,'MinStepsize', 1e-5);  
opt=contset(opt,'InitStepsize', 0.1);  
etc
```